Specialist Profits and the Minimum Price Increment

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Abstract

NYSE specialist participation rates and profits are affected by the rules that govern their trades. The decrease in the minimum price increment from $\$^1/_{16}$ to \$0.01 effectively relaxed the public order precedence rule, gave specialists more price points within the bid-ask spread on which to quote aggressively, and narrowed spreads significantly. As a result, we find that participation rates and high frequency trading profits increased for specialists handling low price stocks (where the $\$^1/_{16}$ cost of obtaining order precedence was relatively expensive) and stocks that formerly traded with few intra-spread price points. Tighter spreads decreased profits for the other stocks.

Keywords: Decimalization, New York Stock Exchange specialists, tick size, trading profits, public order precedence rule, unequally spaced spectral analysis.

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Decimalization changed the trading environment in which New York Stock Exchange specialists trade. The associated decrease in the minimum price variation from $\$^1/_{16}$ to \$0.01 relaxed the public precedence rule, gave specialists more price points between the bid and ask on which to quote aggressively, and narrowed spreads significantly. Although changes in many aspects of market quality have been widely reported, the effect of decimalization on market makers has not been studied in detail.

This paper examines how decimalization affected specialist participation rates and trading profits in over 1,800 NYSE-listed stocks. Since decimalization most likely influenced short term trading strategies, we decompose specialist profits into components associated with various trading horizons using the spectral decomposition method introduced by Hasbrouck and Sofianos (1993), and a generalized method for unequally spaced data that we developed. Using these components, we estimate several cross-sectional regressions to test hypotheses regarding the determinants of the change in specialist participation and profits.

Our results indicate that participation rates and high frequency trading profits increased for specialists handling low price stocks for which the $\$^1/_{16}$ tick made stepping ahead relatively expensive and actively traded stocks for which tight spreads severely constrained specialist trading opportunities.[1] Tighter spreads following decimalization decreased specialist profits in the other stocks.

These results are important because regulators must balance the benefits specialists provide to the market with the costs they impose on the market through their special privileges. Regulators therefore need to know how decimalization affected specialist obligations and privileges, and they must understand how these effects vary across stocks. These issues should also interest investors who trade with specialists and dealers who compete with specialists.

The remainder of this article is organized as follows. Section 1 develops the hypotheses examined in this study and section 2 provides a brief review of related literature. We describe our data in section 3. Results concerning specialist participation rates and specialist profits

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[1] Throughout the paper we use the term "stepping ahead" to indicate when a specialist offers to trade at a better price to obtain order precedence.

respectively appear in sections 4 and 5. Section 6 concludes with a short summary and a discussion of the public policy implications of our results.

1. Decimalization and Specialist Profits

Specialists assume special obligations and receive special privileges to facilitate trade. They must quote continuous markets and they must trade when no one else is willing to do so. Specialists are willing to provide these services because their unique positions allow them to observe all incoming limit and market orders and to use this private information to their advantage when trading. To ensure that specialists will not abuse these privileges, Exchange rules prevent them from trading at certain times or prices.[2]

The public order precedence rule prohibits specialists from trading at the same price at which standing agency orders could be filled. Specialists who wish to trade ahead of agency orders therefore must trade at superior prices. This rule promotes confidence in the markets by assuring public investors that the trading process is fair. The decrease in tick size associated with decimalization, however, essentially repealed the public order precedence rule by significantly lowering the cost of obtaining order precedence through price priority.

NYSE Rule 104 prohibits specialists from taking liquidity that public traders could otherwise take. In practice, this rule prevents specialists from trading with limit orders on their books. Consequently, specialists can generally trade only when filling incoming marketable orders. When specialists are impatient to trade, they try to attract market orders by quoting aggressively. However, they are not allowed to quote prices that equate the bid and ask prices (a 'locked' market). Specialists therefore cannot quote aggressively when the bid/ask spread in their limit order books is only one tick. Decimalization allows specialists to quote more aggressively by increasing the number of potential price points between the bid and offer.

Perhaps the most important constraint on specialist trading comes from the competition of other traders who offer liquidity. Like specialists, public traders can quote aggressively by placing limit orders at improved prices. Decimalization has allowed public limit order traders to substantially decrease bid/ask spreads.

[2] Chapter 24 of Harris (2003) provides a complete survey of specialist trading systems, obligations, and privileges.

Decimalization relaxed constraints on specialist trading activity through the effective repeal of the public order precedence rule and the provision of additional intra-spread price points. However, the narrowing of spreads by public liquidity providers tightened an important constraint. Relaxation of the first two constraints should have increased specialist trade participation rates and profitability whereas the tightening of spreads should have had an adverse impact on these variables. The empirical analyses in this study disentangle these conflicting effects by identifying two important stock characteristics that cause the constraints discussed above to vary across stocks.

The first characteristic, stock price, is most closely related to the public order precedence constraint. Since the minimum price increment is constant for all stocks, the total cost of obtaining precedence through price priority for a trade of a given dollar size is inversely related to the stock price. Although decimalization lowered this cost for all stocks, the economic impact, measured as a percentage of dollar trade size, was greatest for low price stocks. Accordingly, changes in specialist participation and specialist profits should be inversely related to stock price.

The second characteristic, intra-spread price points, is closely related to the Rule 104 constraint. Specialist trading is more constrained when few or no price points are between the best bid and offer than when many such price points exist. Accordingly, changes in specialist participation and specialist profits should be greatest for stocks that formerly were most commonly quoted with a one-tick spread but which now are commonly quoted with a multi-tick spread.

We expect the effect of these two characteristics should not equally influence all specialist-trading strategies. The ability to obtain precedence at lower cost primarily benefits short-term specialist trading strategies rather than long-term speculative strategies. Accordingly, we use spectral methods to decompose specialist-trading profits into those associated with various trading horizons. We follow Hasbrouck and Sofianos (1993) and select horizons based on transaction time, but also expand upon their work and decompose profits by calendar time to ensure that our results identify profits from strategies that may operate in either time domain. We then separately analyze the effect of the above two characteristics on profits at each trading horizon.

Our analyses explain how changes in specialist participation rates and profits following decimalization depend on price and intra-spread price points, after controlling for changes in spreads and other variables known to affect specialists trading behavior and profits. Controlling for these other effects is important in this one-shot event study. Although these controls allow us to place greater confidence in our time-series results, we are most confident in our cross-sectional results because of the specificity of our experimental design to the decimalization hypotheses.

2. Relation to Previous Studies

Our study extends two lines of research. The first considers specialist profits and participation while the second considers the effect of tick size on market quality and the welfare of different market participants.

Madhavan and Smidt (1991) initiated modern quantitative studies into specialist trading behavior with their examination of the inventories of 16 stocks from a single specialist firm. Hasbrouck and Sofianos (1993) decompose specialist profits in 137 stocks across a three-month period ending January 1991 and find that most profits are due to their short term trading strategies. Madhavan and Sofianos (1998) examine all NYSE securities using one month of data from July 1993 and find that listed firm size, block and non-block volume, and return volatility largely explain cross-sectional differences in specialist participation rates. In contrast to these studies, we focus on cross-sectional variation in the *changes* in specialist participation and in high frequency profits associated with a decrease in the minimum price increment. In doing so, we also provide additional evidence regarding the relative importance of different specialist trading strategies and the cross-sectional determinants of specialist participation.

Our study is also related to those exploring the effect of minimum price increments on market quality. Harris (1994, 1997, 1999) argues that tick size reductions will result in smaller spreads, less depth at the best bid and offer, and more transactions inside the spread. Numerous studies have confirmed these predictions. Goldstein and Kavajecz (2000) report that spreads and depth both declined following the 1997 tick size reduction from $\$^1/_8$ to $\$^1/_{16}$. Due to the decrease in depth, Jones and Lipson (2001) report that execution costs increased for large limit orders (greater than 10,000 shares) placed by institutions. Following decimalization, Bessembinder (2002) finds that quoted spreads, effective spreads, and return volatility all decrease. Edwards and Harris (2003) examine 71 stocks and find that individual (as opposed to institutional) limit order fill rates remain largely unchanged.[3]

Two studies examine the effects of tick size on specialist behavior and profits. Ronen and Weaver (2001) examine 357 AMEX stocks following the change to sixteenths, and find that specialist participation rates increased without an increase in trading profits, which they measure indirectly from the effective spreads of specialist trades. Edwards and Harris (2003) find that NYSE specialists increased their participation inside the quote after price decimalization. Our study differs from theirs in several dimensions. Using a cross-sectional sample of over 1,800 stocks, we examine actual trading profits, we decompose those profits into high frequency trading profits, and we identify separate effects of decimalization on participation and profits due to the decrease in spreads, decrease in the cost of stepping ahead, and the availability of additional intra-spread price points.

3. Data

We obtain our sample by combining NYSE Trade and Quote (TAQ) files with NYSE Consolidated Equity Audit Trail (CAUD) files. Along with many trade details, the CAUD files allow us to determine whether the specialist was a buyer or seller on each trade. Using this information, we measure specialist participation rates and profits in each stock. The TAQ data provides the best quote at the time of each trade, which allows us to determine the rate and degree of specialist price improvement.

The sample includes two three-week periods before and after the final decimalization of prices on January 29, 2001. The pre-decimalization sample contains 15 trading days from December 4 to December 22, 2000, and the post-decimalization sample contains 15 trading days from February 26 to March 16, 2001.[4] The two samples are about one-month removed from January 29 to ensure our results reflect learning by any market participant that occurred immediately following decimalization.

The sample includes all NYSE common stocks except foreign listings (ADRs, GDRs, and Canadian stocks), stocks that split between December 4, 2000 and March 16, 2001, stocks for

[3] See also Bacidore (1997), Bacidore et al. (2003), and Battalio and Jennings (2002) among others that examine changes in spreads and order characteristics after a tick size change.
[4] Edwards and Harris (2003) study the same set of 3-week sample periods.

which the average pre- or post-decimalization price exceeded $200, stocks for which we could not explain extreme changes in share volume or returns (7 stocks), and stocks that were included in the pilot decimal trading program.[5] The final sample includes 1,811 common stocks.

3.1 Sample Characterization

The NYSE lists a small number of relatively large stocks and a large number of relatively small stocks. Our sample, which includes most NYSE common stocks, therefore has a similar distribution. The largest one hundred stocks represent roughly 65% of the sample's total capitalization, while the smallest 1,311 stocks represent less than 10% of the total capitalization (Figure 1).

Since specialist-trading strategies depend on the trading activity in their stocks, and since activity is correlated with firm size, we divide our sample into three size categories: large stocks (the top 100), mid-cap stocks (the next 400), and small stocks (the remaining 1,311).[6] The segmentation of our analyses by size allows us to identify differential effects of decimalization across large and small stocks.[7]

We compare price, return, spread, and trading activity variable distributions from the pre- and post-decimalization periods in Table 1. For each variable, we provide the cross-sectional mean and median of the individual stock means. Additionally, we present the associated cross-sectional paired t-test of the mean pre- and post-decimalization differences, and the Wilcoxon *Z*-score for the median differences. We present statistics regarding specialist participation rates and profits in the following sections.

We compute market capitalization as the mean trade price during the December 2000 three-week sample period times the number of shares outstanding. The cross-sectional mean market capitalization rises from $550 million for small stocks to $63.7 billion for large stocks

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[5] The decimal pilot stocks traded on pennies in both of our sample periods. We separately analyzed these stocks to confirm that the empirical results reported in this study are not due to unidentified phenomena that are unrelated to decimalization. We discuss the results of these tests below.

[6] We were reluctant to segment by dollar volumes because volumes may be endogenous. The very high cross-sectional correlation between dollar volumes and capitalization ensures that the results would be the same.

[7] We also analyzed the full sample using equal- and value-weighted analyses. The equal-weighted analyses produced results similar to the equal-weighted small stock sample, while the value-weighted analyses produced results similar to the large stock sample. We choose to present size-segmented results instead of these value-weighted results because regulators and practitioners will make better decisions based on segments than on averages.

(Panel A). Since we exclude all stocks that split shares, the post-decimalization change in market capitalization is proportional to the post-decimalization change in price.

Price levels rise across the size-sorted stock groups from just under $20 for the small stocks to slightly over $50 for the large stocks. The large stock sample has no stocks priced under $10. Since the cost of stepping ahead decreases with the inverse of price, the cross-sectional variation in this cost is small for high price stocks. Inverse price therefore should not be an important determinant of post-decimalization changes in specialist participation and in specialist profits for high price stocks.

The prices of small and mid-cap stocks rose between our two samples while the prices of the large stocks fell. These changes reflect different returns earned between our sample periods and should have little effect on our study.

Returns during the post-decimalization period were significantly lower for each of the stock groups than in the pre-decimal period. The mean difference in returns is –4.3 percentage points (from 1.8% to –2.5%) for small stocks and –10.3 percentage points (from 3.6% to –6.7%) for large stocks. Since price returns may determine the profitability of some specialist trading strategies—especially long-term strategies, we cannot attribute all changes in specialist participation rates and specialist profits to decimalization. Fortunately, the different returns should not affect our tests of the cross-sectional implications of decimalization for participation rates and trading profits. Our results are less sensitive to the return difference than one might first suspect because we focus on high frequency profits and because we assume inventory is initially zero at the beginning of the sample periods when computing specialist-trading profits.

Daily return standard deviations decreased for each stock group, but by no more than seven-tenths of a percentage point. Although the difference is statistically significant in the cross-section, we are reluctant to attribute this change to decimalization because of the substantial time-series variation in volatility. However, we control for this change in the cross-sectional tests since volatility affects the profitability of short term trading strategies.[8]

[8] Madhavan and Sofianos (1998) find that cross-sectional variation of specialist participation is positively related to volatility. In more volatile markets specialists are more likely to provide liquidity in a one-sided market (an affirmative obligation), and there may be more opportunities to profit from any short-term momentum or reversion.

Average spreads, measured in ticks, increased from 2.3 sixteenth-dollar ticks to 10.8 penny-ticks following decimalization for small stocks and from 2.2 to 8.7 ticks for large stocks (Panel B). The number of prices at which a specialist can gain order precedence by offering a better price thus increased significantly.

As is now well known, absolute dollar and relative spreads declined significantly following decimalization. In our small stock sample, the mean quoted spread fell from 14.4 to 10.8 cents and the mean effective spread dropped from 10.1 to 7.7 cents. For large stocks, quoted spreads fell from 13.5 to 8.7 cents and effective spreads dropped from 8.6 to 5.9 cents. We control for the change in spreads in our cross-sectional regressions because smaller spreads should reduce profits, all else constant.[9]

The average fraction of total trading time that a stock's spread equaled a one sixteenth-dollar tick was 30.9 percent before decimalization for small stocks and 40.9 percent for large stocks (Panel B, last set of rows). Following decimalization, small stocks were quoted with a one-penny spread only 6.1 percent of the time, and large stock spreads were one penny 11.0 percent of the time. For all firms, specialist trading was far less constrained by the minimum tick following decimalization.

Finally, the mean number of transactions per day increased significantly for each stock group (Panel C). However, small stock share volume decreased significantly while large stock share volume remained essentially unchanged. Together, these results imply that trade size decreased. Consistent with evidence reported by Goldstein and Kavajecz (2000) and Jones and Lipson (2001), these results suggest that traders became more likely to break large orders into small trades. To assess the changes in the composition of trading volume, we follow Madhavan and Sofianos (1998) and partition total volume into block volume (trades ≥ 10,000 shares) and non-block volume (trades < 10,000 shares).[10] While block volume decreased across all stock groups (significantly for the small and mid-cap stocks), non-block volume remained largely

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[9] To avoid outliers, we applied typical filters to the data before computing mean spreads. We deleted observations if the quoted spread exceeds $5; if the transaction price is more than 12.5 cents greater (less) than the ask price (bid price); or if the transaction, bid, or ask price is more than 25% larger than (or less than 75% of) the preceding transaction, bid, or ask price respectively. We also deleted trades reported before 9:30 AM or after 4:01 PM, and trades with a CAUD correction code greater than 2 (we use only 'original good,' and 'original corrected' trades). As in Bessembinder (2003), we match trades to quotes without the time adjustment proposed in Lee and Ready (1991).
[10] We also identified block volume as the number of shares originating in each stock's largest 2.5% of orders. All cross-sectional inferences are unaffected by the choice of block definition.

unchanged for small stocks but increased significantly for large stocks. We control for changes in block and non-block volume since they are likely to alter specialist participation and profit.

4. Specialist Trade Participation Rates

The specialist trade participation rate is the fraction of all trades in which the specialist either buys or sells. As expected, the average specialist trade participation rate increased from 35.9 percent to 43.3 percent for small stocks following decimalization (Table 2, first set of rows). The large stock participation rate also increased from 24.3 percent to 30.0 percent.[11]

We expect that the post-decimalization change in participation rate should be inversely related to stock price. We provide univariate evidence of this relation by sorting each size-sorted sample into three subsamples based on price. We classify stocks priced $10 or less as low price stocks, those over $25 at high price stocks, and the remainder are mid price stocks. Since the post-decimalization reduction in the cost of stepping ahead was large for the low price stocks but trivial for the high price stocks, the greatest increase in specialist participation should be for the low price stocks. The results confirm this conjecture. For small stocks, the rate of trade participation increased by 10.8 percentage points for stocks priced under $10 whereas it increased only by 3.6 percentage points for stocks priced over $25 (Table 2, Panel A). Similarly, the trade participation rate for mid-cap stocks increases by 13.4 percentage points for stocks priced under $10, but by only 3.8 percentage points for stocks priced over $25. We obtain similar results for the large stocks even though this sample contains no stocks priced under $10 and only six stocks priced under $25.

For each stock we also calculate the percent of specialist trades executed at the current quote, inside the quote, and outside the quote (the sum of which must add to 100). Specialists trading firms of all size increased their participation rates primarily by trading more often inside the current quote (Table 2, Panel B). Before decimalization, roughly 44% of all specialist trades in small stocks occurred at the quote with virtually all of the remainder inside the quote. After decimalization, specialist trades at the quote fell by roughly 10 percentage points, while the

[11] We also report specialist participation rate by their fraction of all shares traded. This measure produces lower participation rates than does the rate measured as a fraction of transactions, but both measures produce qualitatively identical results in all our analyses.

fraction inside the quote increased by 10%.[12] Interestingly, the change in the distribution was roughly the same across stock price and market capitalization levels as well. To summarize, the univariate evidence indicates that participation increased (especially for low price stocks) and that the increase is due to more trades inside the current quote.

We obtain a more rigorous test of the dependence of the post-decimalization change in specialist participation on price level and intra-spread price points by estimating a cross-sectional regression that controls for changes in other determinants of specialist participation. The independent variables of greatest interest are the inverse price, *InvPrice*, which is proportional to the change in the cost of obtaining precedence, and the change in the time-weighted average of the inverse spread in ticks, *ΔInvSpreadInTicks*, which characterizes the change in step-in-front opportunities. We use the change in the inverse spread (in ticks) instead of the change in spread (in ticks) because a change from one tick to two ticks represents a much more valuable increase in trading opportunity than does a change from ten ticks to eleven ticks. The greater is *ΔInvSpreadInTicks*, the greater is the increase in opportunity for a specialist to obtain order precedence.[13]

Madhavan and Sofianos (1998) report that return volatility, block volume, and non-block volume largely determine cross-sectional variation in specialist participation rates. We therefore include changes in these variables to control for variation that is not due to decimalization. We also include the change in the total return to determine whether specialist participation might be correlated with market movements. Our full regression model is

$$\begin{aligned}(1)\qquad \Delta ParticiRate_i = \beta_0 + \beta_1 InvPrice_i + \beta_2 \Delta InvSpreadInTicks_i + \beta_3 \Delta Volatility_i + \\ + \beta_4 \Delta NonBlockVolume_i + \beta_5 \Delta BlockVolume_i + \beta_6 \Delta Return_i + \varepsilon_i\end{aligned}$$

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[12] The increase in percent of specialist trades inside the quote is slightly less than the decrease in specialist trades at the quote, which indicates a slight increase in trades outside the quote. This increase is probably due to greater quote-matching errors caused by "flickering quotes." It may also be due to an increase in trades outside the quotes when there is insufficient depth at the best bid or offer. In these cases, any orders at the quote execute at their limit prices. In any event, the percent of trades outside the quote never exceeds 2%.

[13] As an alternative to *ΔInvSpreadInTicks,* we also used *ΔFracTimeOneTick*, which measures the change in percent of time that the spread is at one tick. Both variables measure the change in opportunities available for the specialist to quote aggressively. Since these variables are highly correlated (correlation = 0.89), and since the results are not significantly altered, we report all tests using only the former measure.

where *ΔParticiRate* is the change in specialist participation rate, *ΔVolatility* is the change in daily percent return standard deviation (returns are measured in percent), *ΔReturn* is the change in return, and ε is the regression error term.

The error term in this regression has two components. One component is due to normal variation in the fit of the model while the other component is due to noise in our estimates of the change in specialist participation rates. We therefore assume that the error term is independently distributed with variance

$$\sigma_i^2 = \tau^2 + \left(\frac{r_{1,i}\left(1-r_{1,i}\right)}{N_{1,i}} + \frac{r_{2,i}\left(1-r_{2,i}\right)}{N_{2,i}} \right). \tag{2}$$

The first term is a standard regression error variance common to all observations while the second term is due to the estimation error associated with computing *ΔParticiRate*. The two terms in parentheses are the binomial error variances of the time-series estimates of the specialist participation rates in the pre- and post-decimalization periods, which we denote by 1 and 2 for brevity. The variables in the numerator are the participation rates and those in the denominator are the total number of trades. The unusual error structure requires that we estimate the model using the maximum likelihood method.

Maximum likelihood coefficient estimates based on each of the three stock size groups appear in Table 3. The positive coefficients for *InvPrice* indicate that participation rates increased with the decrease in the costs of stepping ahead. This relation is significant for the small and mid-cap stocks, but insignificant for the larger stocks for which their high prices made the change in the step-ahead cost trivial. The significant positive coefficient estimates for *ΔInvSpreadInTicks* in each regression indicate that participation increased with the available number of intra-spread price points. The signs of the estimated coefficients for block volume (-) and non-block volume (-) are the same as those estimated by Madhavan and Sofianos (1998) in their cross-sectional regression of participation levels.[14]

[14] We also estimated the model using OLS. Our results were qualitatively similar, though statistically somewhat less significant. The maximum likelihood results are more significant because stocks for which the dependent variable is poorly estimated are given less weight.

The change in return variable is negative and significant for mid-cap and large firms. Specialists apparently participated more when prices fell significantly in these stocks in our post-decimalization sample period. The average returns in this period were –2.5, –3.6, and –6.7 percent respectively for the small, mid-cap and large stocks. Their increased participation while the market was dropping is consistent with their affirmative obligations.

Consistent with our arguments, the increase in participation rates is greatest for low price stocks and for stocks with the largest increase in the number of intra-spread price points. We examine whether these changes in participation yielded significant changes in profit in the next section.[15]

The estimated intercept coefficients for all three stock group regressions are significantly negative. If the control variables in the regression adequately control for all factors that significantly determine specialist participation, we can interpret this result as follows. Following decimalization, specialist participation rates would have dropped if specialists could not have stepped ahead at decreased cost and if they could not have taken advantage of the additional price points.[16] The drop in specialist participation would have been due to increased competition from limit order traders and their tightening of the spreads. The estimated intercept coefficients indicate by how much specialist participation rates would have decreased if decimalization had not relaxed the negative obligations. Specialist participation would have dropped by roughly 9, 13, and 14 percentage points, respectively for small, mid-cap, and large stocks.

5. Specialist Profits

We begin this section with a brief analysis of the changes in the effective spreads that specialists earned on their trades. We then discuss the measurement of their actual trading profits and the spectral decomposition of these profits by trade and calendar time horizons. We conclude by presenting our cross-sectional analyses of changes in specialist profits at various time horizons.

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[15] As a control experiment, we estimated the same regression using the decimal pilot stock sample. In this sample, the change in participation is unrelated to *ΔInvSpreadInTicks* and negatively related to *InvPrice*. The sign and qualitative significance of the control variables is the same as observed for our primary samples. Our primary results thus are not likely due to unidentified phenomena that are unrelated to decimalization.

[16] Analysts usually do not make inferences from regression intercepts because the intercepts depend on the means of the independent variables. In this model, these means are mean changes in the variables that determine profits. The intercept reflects these mean changes, which is exactly what is necessary to control for the effects of these variables.

5.1 Specialist Effective Spreads and Price Improvement

As discussed above, decimalization decreased quoted spreads and increased the fraction of trades that specialists made inside the quote. These results imply that the effective spreads or the price improvements that specialists offered traders decreased following decimalization.[17] Both decreased in all three of our stock size groups (Table 4, Panel A). The mean effective spread respectively decreased by 1.1, 1.6 and 1.5 cents for small, mid-cap, and large stocks. The mean price improvement likewise decreased by 2.9, 3.3 cents and 3.9 cents.

Interestingly, the mean effective spread for those trades that occurred inside the spread increased by 1.4, 1.0, and 0.9 cents for small, mid-cap, and large stocks, respectively. The one-penny price increment allowed specialists to offer less price improvement when stepping in front of the quote.

The effective spread for specialist trades decreased least for low price stocks (Table 4, Panel B). For small stocks, the mean change is –0.5 cents for stocks priced under $10 and –1.8 cents for stocks priced over $25. The difference is due in part to the increase in the effective spread for specialist trades executed inside the quote. This spread increased slightly more for low price small stocks (+1.9 cents) than for high price small stocks (+0.8 cents), while the decrease in dollar price improvement was slightly greater for the low price small stocks (-3.0 cents versus -2.4 cents). The mid-cap and large stock groups also exhibit a similar relation between effective spreads and price improvement.

5.2 Measurement of Specialist Profits

Specialist profits are the difference between their trading profits and the direct costs that they incur making markets. Since their direct costs did not likely change much over the short sample period, any change in profits due to decimalization should be almost exclusively due to a change in their trading profits.

We compute specialist trading profits by tracking changes in the value of their inventories. Following Hasbrouck and Sofianos (1993), we measure trading profits on a mark-

[17] The effective spread is twice the difference between the trade price and the midpoint of the bid and ask prices. Price improvement is the difference between the trade price and the bid or ask price that the specialist's customer would have received had the trade occurred at the best bid or offer. The total quoted spread thus is the effective spread plus twice the price improvement.

to-market basis. Let p_t denote the transaction price at time t, and let n_t denote the number of shares held by the specialist at time t. The mark-to-market profit at time t is the change in the market value of the specialist inventory,

$$(3) \qquad \pi_t = n_{t-1}\left(p_t - p_{t-1}\right),$$

so that total profit in any given period is the sum of π_t in that period.

Since we do not know initial inventories, we take them to be zero at the beginning of the pre- and the post-decimalization sample periods. We therefore do not measure actual specialist trading profits, but rather the difference between their actual trading profits and the mark-to-market profits from holding their initial inventory positions. This issue should not seriously affect the results because we expect that decimalization primarily affected high frequency profits. Since we lack data on operational expenses and commission revenue, we examine only trading profits and not net specialist profits.

Following decimalization, the median gross profit per day for specialists handling small stocks increased insignificantly from $2,200 to $2,300 (Table 5). In contrast, the median gross profit declined by $33,900 for mid-cap stocks and was essentially unchanged for large stocks. The decline in mean gross profits was significant for both mid-cap and large stocks. This evidence is consistent with specialists profiting from the relatively greater cost reduction associated with step-ahead strategies in low price stocks. The decrease in the average profits in the high price stocks probably reflects their increased participation in the falling market of that period.

For comparison purposes, we note that Hasbrouck and Sofianos (1993) report a median gross profit of $7.55 per trade across their entire sample. Across our entire sample 1,811 stocks, we find that the median gross profit per specialist trade fell from $17.58 to $12.66 following decimalization.[18] The difference in profit per trade between the two studies is likely due to different samples (Hasbrouck and Sofianos study a capitalization-stratified random sample of 137 stocks over the 3-month period ending January 1991), different minimum tick sizes (the minimum tick in 1991 was $\$^1/_8$) and different market conditions.

[18] The percentage decrease in median profit per trade is larger than the percentage decrease in gross profit per day because of the increase in the number of transactions per day and the rise in the specialist participation rate.

We do not dwell on gross profits, however, because their variation largely depends on long run phenomena. Since we expect that the reduction in tick size will primarily affect the profitability of short term trading strategies, we turn now to the decomposition of trading profits.

5.3 Decomposition of Specialist Profits

Specialists often engage in long term speculative trading strategies in addition to the high frequency trading strategies normally associated with dealing. Both types of trading contribute to their profits, but decimalization probably only affects profits due to their high frequency trading strategies. Accordingly, we use spectral methods to decompose specialist profits into high, medium, and low frequency components following, and expanding upon, Hasbrouck and Sofianos (1993).

5.3.1 The Hasbrouck and Sofianos Decomposition

The appendix to Hasbrouck and Sofianos (1993) provides a detailed description of the spectral decomposition of profits using real analysis. We briefly restate their analysis using linear algebra since many people will find the intuition easier to understand using these methods.

Any data series x_t of length n can be represented as

(4) $$x_t = \sum_{k=0}^{m} \left(\alpha_k \cos\left(\omega_k t\right) + \beta_k \sin\left(\omega_k t\right) \right)$$

where $m = n/2$ if n is even and $\left(n-1\right)/2$ otherwise, $\omega_k = 2\pi k/n$ are the Fourier frequencies, k counts the number of waves of the associated frequency that span the sample, and $\left\{\alpha_k\right\}$ and $\left\{\beta_k\right\}$ are the Fourier coefficients. For expositional convenience, assume that n is even. The Fourier coefficients generally are obtained using specialized algorithms such as the Fast Fourier Transform, but in principle they can be obtained simply by solving the following linear equation:

(5) $$\mathbf{x} = \left[\mathbf{C} \quad \mathbf{S}\right] \begin{bmatrix} \boldsymbol{\alpha} \\ \boldsymbol{\beta} \end{bmatrix} \equiv \mathbf{Tc}$$

where $\mathbf{x}$ is the $n \times 1$ data series vector, $\mathbf{C}$ is the $n \times \left(m+1\right)$ matrix $\cos\left(\mathbf{t}\boldsymbol{\omega}_k\right)$, $\mathbf{S}$ is the corresponding $n \times \left(m+1\right)$ matrix of sines, $\mathbf{t}$ is the $n \times 1$ column vector of the equal-spaced series $\left\{1:n\right\}$, $\boldsymbol{\omega}_k = 2\pi\mathbf{k}/n$ is the $1 \times \left(m+1\right)$ row vector of the frequencies, $\mathbf{k}$ is the $1 \times \left(m+1\right)$ row vector of the series $\{1:(m+1)\}$, and $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ are $(m+1)\times 1$ vectors of $\{\alpha_k\}$ and $\{\beta_k\}$. The Fourier coefficients thus are simply a linear transform of the data series.[19]

The key to understanding the Hasbrouck and Sofianos profit decomposition is to note that the columns of the trigonometric matrix $\mathbf{T} = [\mathbf{C} \quad \mathbf{S}]$ are orthogonal, so that any dot product of one column with any other is zero.[20] Recall from equation (3) that specialist profits are the product of the change in price with the previous inventory position. Total profit therefore is the dot product of the vector of lagged inventories with the vector of price changes. Let these vectors be called **x** and **y** and let their Fourier transforms be $\mathbf{c}^{\mathbf{x}}$ and $\mathbf{c}^{\mathbf{y}}$ so that $\mathbf{x} = \mathbf{T}\mathbf{c}^{\mathbf{x}}$ and $\mathbf{y} = \mathbf{T}\mathbf{c}^{\mathbf{y}}$. Their dot product is $\mathbf{x}'\mathbf{y} = \mathbf{c}^{\mathbf{x}\prime}\mathbf{T}'\mathbf{T}\mathbf{c}^{\mathbf{y}}$. Since the columns of **T** are orthogonal, the matrix $\mathbf{T}'\mathbf{T}$ is a diagonal matrix so that

(6) $$\mathbf{x}'\mathbf{y} = \sum_{k=0}^{m} \left(\mathbf{C}_k'\mathbf{C}_k \alpha_k^x \alpha_k^y + \mathbf{S}_k'\mathbf{S}_k \beta_k^x \beta_k^y \right)$$

where $\mathbf{C}_k$ and $\mathbf{S}_k$ are the k^{th} cosine and sine columns of **T**. The dot product $\mathbf{x}'\mathbf{y}$ thus is a weighted sum of the products of the Fourier coefficients of **x** with those of **y** for each *k*. In spectral terminology, these *k* terms constitute the cross-spectrum.

Following Hasbrouck and Sofianos (1993), we identify as high frequency profits the sum of all *k* terms whose corresponding wavelength is less than or equal to 10 trades. We likewise identify medium and low frequency profits as the sums of those *k* terms with corresponding wavelengths of 11 to 100 trades, and more than 100 trades.[21] These identifications derive their meaning from the time-structure associated with the Fourier representations of the inventories and the associated price changes. We do not assume that deterministic cyclic processes generate

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[19] The trigonometric transform matrix **T** is of rank *n*. Since it has *n* + 2 columns if *n* is even and *n* + 1 columns if *n* is odd, the generalized inverse must be used to identify the Fourier coefficients using linear algebraic methods. The additional columns come from the zero frequency components, which are column vectors of ones for the cosine and of zeros for the sine. The zero frequency cosine thus represents the series mean.

[20] The columns are orthogonal because the sine and cosine waves are never in synch with each other (and therefore uncorrelated), they all have different frequencies, they are evaluated at equal intervals, they each cycle a whole number of times over the sample, and the sine and cosine at a given frequency are orthogonal.

[21] These cutoffs occur at $k_{Med} = 2m/10$ and $k_{Low} = 2m/100$. When these formulas do not yield integer values, we interpolate over *k* to sensibly assign the cross-spectral weights of the *k*'s to the two adjacent frequency bands. For example, if $k_{Med} = 50.4$, we assign all cross-spectral weight for $k = 50$ to medium frequency profits, 40 percent of

the data. Instead, we use spectral methods only to transform the data to facilitate their useful interpretation.

5.3.2 The Generalized Decomposition

The relation between trading time and calendar time differs substantially across stocks. For the most actively traded stocks, 10 specialist trades may occur within a few minutes or less. For the least actively traded stocks, 10 specialist trades may occur over several days. Since specialist-trading strategies may operate in both trading time and calendar time domains, we also decompose profits by calendar time horizons.[22]

To ensure that our analyses are truly calendar time analyses, we drop the assumption implicit in standard spectral analyses that the observations are equally spaced in time.[23] Unfortunately, although we can compute Fourier transforms in calendar time for unequally spaced data by using the generalized inverse to solve (5) with **T** computed from unequally spaced **t**, the columns of the cosine and sine matrices are not orthogonal when the data are not equally spaced. Since orthogonality is essential to obtain an additive decomposition of profits across frequencies, we cannot use this approach. Instead, we use linear orthogonal projections to generalize the Hasbrouck and Sofianos method to allow for uneven spacing of the trades through time. Our method is a generalization because it exactly produces the Hasbrouck and Sofianos results when the data are equally spaced.

Specifically, we use OLS regression methods to estimate the following model:

(7) $$x(t) = \sum_{k=1}^{k_{Med}} \left(\alpha_k \cos(\omega_k t) + \beta_k \sin(\omega_k t) \right) + \varepsilon(t)$$

where k_{Med} is the cutoff *k* (specified below) that separates medium frequencies from high frequencies and *t* is now an index that runs from 0 to *n* upon which the trade times are mapped. For mapping purposes, *t* is 0 at 9:30 AM on the first day of the sample period and *t* is *n* at 4:00

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the cross-spectral weight for $k = 51$ to medium frequency profits, and the remainder of the cross-spectral weight for $k = 51$ to high frequency profits.

[22] Harris (1986 and 1987) and the papers cited therein discuss how trade time and calendar time differ.

[23] We could translate from trading time to calendar time by assuming that the trades are equally spaced in time and identify the cutoff *k* values that correspond, on average, to calendar horizons. This approach transforms a trade time domain approach to calendar domain approach only by varying the cutoff *k* values. The approach described in this section is a true calendar domain approach.

PM on the last day of the sample period. We concatenate trading days so that 4:00 PM on one trading day and 9:30 AM on the next trading day correspond to the same t.[24] Thus, a trade that takes place at 11:30 AM on the first day of our 15-day sample in a stock that has 300 total specialist trades would be assigned a value of $t = 6.154$ (2 hours into the first day divided by 6.5 hours per day divided by 15 days in the sample period times 300 trades in the sample.)

The linear algebra representation of (7) is

$$\text{(8)} \qquad \mathbf{x} = \begin{bmatrix} \mathbf{C}_{Low\&Med} & \mathbf{S}_{Low\&Med} \end{bmatrix} \begin{bmatrix} \boldsymbol{\alpha}_{Low\&Med} \\ \boldsymbol{\beta}_{Low\&Med} \end{bmatrix} = \mathbf{T}_{Low\&Med}\mathbf{c}_{Low\&Med} + \boldsymbol{\varepsilon}_{High}$$

where $\mathbf{C}_{Low\&Med}$ and $\mathbf{S}_{Low\&Med}$ consist of the first $k_{Med} + 1$ columns of **C** and **S**, which are now computed from the unequally spaced series of times **t**. The OLS estimated residual of this regression, $\hat{\boldsymbol{\varepsilon}}_{High}$, is the high frequency component of **x**. It represents the variation in **x** that cannot be explained by the low and medium frequency sines and cosines in $\mathbf{T}_{Low\&Med}$.

To obtain the medium and low frequency components of **x**, we use OLS to estimate the following model:

$$\text{(9)} \qquad \mathbf{x} - \hat{\boldsymbol{\varepsilon}}_{High} = \begin{bmatrix} \mathbf{C}_{Low} & \mathbf{S}_{Low} \end{bmatrix} \begin{bmatrix} \boldsymbol{\alpha}_{Low} \\ \boldsymbol{\beta}_{Low} \end{bmatrix} = \mathbf{T}_{Low}\mathbf{c}_{Low} + \boldsymbol{\varepsilon}_{Med}$$

where $\mathbf{C}_{Low}$ and $\mathbf{S}_{Low}$ consist of the first $k_{Low} + 1$ columns of **C** and **S**, and k_{Low} is the cutoff k (specified below) that separates low frequencies from medium frequencies. The dependent variable in this regression, $\mathbf{x} - \hat{\boldsymbol{\varepsilon}}_{High}$, is the sum of the low and medium frequency components of **x**. OLS estimation decomposes this sum into the low frequency component $\mathbf{T}_{Low}\hat{\mathbf{c}}_{Low}$ (that depends only on the low frequency sines and cosines) and the medium frequency component $\hat{\boldsymbol{\varepsilon}}_{Med}$ so that $\mathbf{x} = \mathbf{T}_{Low}\hat{\mathbf{c}}_{Low} + \hat{\boldsymbol{\varepsilon}}_{Med} + \hat{\boldsymbol{\varepsilon}}_{High}$. The linear projections ensure that the three components are orthogonal. When the series of times **t** is equally spaced, the regression coefficients produced in these generalized decomposition method are exactly equal to the Fourier coefficients of **x** described above because the columns of **T** are orthogonal.[25]

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[24] Although our method allows us to map overnight periods and weekend periods, we choose not to do so.
[25] Although we use our method only to compute orthogonal decompositions for bands of low, medium and high frequencies, the method can be used to create a fully orthogonal transformation of the original series.

We obtain the calendar time low, medium, and high frequency profits for each stock by using this method to decompose the lagged inventory and price change series. The dot products of these two corresponding series provide the low, medium, and high frequency profits. The three types of profit sum to total profits because the decomposed series are orthogonal.

We identify low, medium, and high frequency profits as the sums of all terms whose corresponding wavelengths are less than or equal to ½ day, ½ to 3 days, and over 3 days. The associated cutoff *k*'s are $k_{Med} = 30$ (15 days divided by ½-day period) and $k_{Low} = 5$ (15 days divided by 3-day period). Unlike the trade time decomposition, these cutoff *k*'s are not proportional to the number of observations in the sample. Accordingly, the model estimates zero high frequency profit when the number of observations is 61 or less, and zero medium frequency profit when the number of observations is 11 or less.[26] We therefore dropped such stocks from our cross-sectional analyses.

5.4 Preliminary Profit Characterizations

Consistent with Hasbrouck and Sofianos (1993), we find that specialist trading profits largely accrue at high frequencies (Table 6). When based on trade time, high frequency (< 10 trades) and medium frequency (10 to 100 trades) profits are greater than zero in each sample period. When based on calendar time, only high frequency (< ½ day) profits are greater than zero, except for the small stocks for which medium frequency profits are also positive. The difference between the trade and calendar domains for the mid-cap and large stocks is due to the fact that their number of trades per ½ day typically exceeds 100. Since small stocks are thinly traded, their positive profits at the medium calendar horizon (< 3 days) may reflect strategies based on trade time, rather than calendar time.

The negative low frequency profits may reflect unprofitable speculation, or the costs of offering liquidity when no one else is willing to offer it. We found that the cross-sectional variance of the low frequency profits is very high, as did Hasbrouck and Sofianos (1993).

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[26] The model uses 61 degrees of freedom to compute the low and medium frequency components. The mean accounts for one degree of freedom and the 30 frequencies for *k* between 1 and $k_{Med} = 30$ each account for two degrees of freedom for their sine and cosine terms.

For mid cap and large firms, the mean post-decimalization decrease in gross profits discussed above was due primarily to decreases in low frequency profits. The near zero change in gross profits for small firms were due to offsetting increases in low frequency profits. These results suggest that most of the gross changes in profits were not related to decimalization.

Following decimalization, high frequency profits decreased in both time domains for stocks of all sizes. However, since this analysis does not control for other factors that affect specialist profits, we are reluctant to attribute this result to decimalization. In particular, we suspect that the decrease in volatility between the two sample periods probably accounts for much of the decrease in high frequency profits. We disentangle these issues in cross-sectional analyses presented below.

Before considering these analyses, note that the mean change in high frequency profits across stock groups is consistent with our cross-sectional hypotheses. The trade time high frequency profits decrease by 7.9, 11.0, and 11.7 percent, respectively, for small, mid-cap, and large stocks. This rank ordering is identical to the rank ordering of these groups by mean stock price. This crude characterization of the cross-sectional variation of the change with respect to price thus conforms to our expectations. A similar pattern appears in the calendar time mean high frequency profits.

5.5 The Change in Specialist Profits Following Decimalization

To obtain a more precise characterization of the cross-sectional effects of decimalization on trading profits, we estimate cross-sectional regression models in which we control for other factors that may affect specialist profits. In particular, we control for changes in volatility, volume, relative spreads and returns.

The dependent variables in these regressions are the changes in profit measured at the various frequencies, scaled by a measure of expected total gross trading profit. We scale the change in profit to account for the fact that gross specialist profits are higher for larger stocks than for smaller stocks (see Table 5). This adjustment ensures that the scale of the dependent variable does not vary by firm size.

We scale by expected total gross trading profit instead of pre-decimalization total gross trading profit because trading profits are quite variable. Had we simply examined the percentage change in profits, much of the variation in the dependent variable would have been due to noise in the pre-decimalization profits in the denominator.[27] Alternatively, we use the predicted value from a non-linear regression of pre-decimalization total profit on market capitalization to estimate expected total trading profit. We assume that expected profit is given by

$$\log \mathrm{E}\left(TotalProfit_t\right) = \alpha + \log \beta\left(MkCap_t\right). \tag{10}$$

Since observed profits are often negative, we estimate

$$TotalProfit_t = \alpha MkCap_t^{\beta} + \varepsilon_t \tag{11}$$

using non-linear ordinary least squares and use $\hat{\alpha} MkCap_t^{\hat{\beta}}$ as the expected total profit estimate.

Our cross-sectional regression model is

$$\begin{aligned} Rel\Delta FreqProfit_i = \beta_0 &+ \beta_1 InvPrice_i + \beta_2 \Delta InvSpreadInTicks_i + \beta_3 \Delta RelSpread_i \\ &+ \beta_4 \Delta Volatility_i + \beta_5 Rel\Delta NonBlockVolume_i + \beta_6 Rel\Delta BlockVolume_i \\ &+ \beta_7 \Delta Return_i + \varepsilon_i \end{aligned} \tag{12}$$

where *RelΔFreqProfit* is the change in a trading profit at a given frequency, and *RelΔNonBlockVolume*, and *RelΔBlockVolume* are the changes in nonblock and block volumes, all expressed relative to expected total profit. In addition to the control variables that appear in the specialist participation rate regression, we also include the change in the mean relative spread (spread as a fraction of price), *ΔRelSpread*, to account for the narrowing of the spreads due to decimalization. We scale the volume variables to ensure that they conform to the dependent variable. We expect that increases in volatility, non-block volume and relative spreads will increase high frequency profits. We do not expect that block volume will be significant because specialists generally do not participate in blocks to the same extent that they participate in smaller trades, especially with respect to high-frequency trading strategies. Finally, we also include the change in return, *ΔReturn*, to account for systematic effects that price movements may have on specialist profits, especially given the large price drop in the post-decimalization period.

[27] Scaling by pre-decimalization profits also would have produced meaningless results when the pre-decimalization profits were negative, and extreme percentage changes when the pre-decimalization profits were near zero.

As with the cross-sectional specialist participation regressions, our key variables are *InvPrice* and *ΔInvSpreadInTicks*. We expect to observe a positive relation with each variable with respect to the change in higher frequency profits since the relative value of decreasing the minimum price increment is greater for low price stocks and for stocks with fewer intra-spread price points.[28]

Like the regression model for specialist participation, this regression model has a dependent variable that includes noise from the time-series data from which we computed it. We can derive the standard errors associated with the decomposed profits by assuming that lagged inventories and current price changes are correlated and jointly independently and identically distributed. The formula depends on the variances of the two variables, their correlation, and the sample size. We did not use this approach because the iid assumption is not reasonable. In particular, bid/ask bounce and mean reversion in inventories impart substantial time structure to the inventories and price changes and thereby inflates their variances. Instead, we assume that the noise in the profit components is proportional to the variance of the total profits, which we estimate as the variance of the mark-to-market profit time-series times its length.[29] In particular, we model the error term variance as a weighted linear sum of a constant and the time-series profit variance, and allow the model to estimate the weights. If estimation places all weight on the constant, the resulting model is OLS. If it places all weight on the time-series variances, the resulting model is GLS. The error term for the high frequency change in profit regression model is

[28] As an alternative to *ΔInvSpreadInTicks,* we also estimated the regression model using *ΔFracTimeOneTick* to measure the change in opportunities to step-ahead, without substantially different results.

[29] We also considered estimating the variances of the three total profit components directly from the mark-to-market profit time series by using spectral methods to decompose the total variance in the mark-to-market profit time series into high, medium and low frequency component variances. Simulation methods confirmed that the variances produced by this decomposition are correct when the lagged inventories and current price changes are correlated and jointly independently and identically distributed. However, an examination of our actual cross-sectional results indicates that the mean estimated decomposed profit variance is much larger than the cross-sectional variance of high frequency profits. Since the former should always be smaller than the latter, it is apparent that time structure in the variables is shifting variance among the components. Using simulation methods, we confirmed that this variance decomposition produces highly biases estimates of the profit variances when the data have any interesting time structure. We also found that the mean estimated decomposed profit variance is much smaller than the cross-sectional variance of low frequency profits. Since the component variances have to add up to the total variance, this result is not informative.

$$\text{(13)} \qquad \sigma_i^2 = \tau^2 + \gamma^2 \left(\frac{N_1 \operatorname{Var}\left(MarkToMkTradeProfit_{1,i} \right) + N_2 \operatorname{Var}\left(MarkToMkTradeProfit_{2,i} \right)}{\left(\mathrm{E} TotalProfit_i \right)^2} \right)$$

where τ^2 is the regression model error, the term in parentheses is assumed proportional to variance of the estimation error in the dependent variable, $\operatorname{Var}\left(MarkToMkTradeProfit \right)$ is the time-series variance of the mark-to-market profits given by (3), and *N* is the number of specialist trades. We used similar expressions in the regression models of medium and low frequency profit changes. The unusual error structure again requires that we estimate the model using the maximum likelihood method.

We estimated the regression for each stock size group using the various trade time and calendar time profits (Table 7, Panels A and B).[30] In both time domains, the estimated relation between high frequency profits and *InvPrice* is positive and significant for small and mid-cap stocks, but not for large stocks. The *InvPrice* coefficient is also positive and significant in the small stock calendar medium frequency (½ day - 3 days) profit regression. Since small stocks are thinly traded, this result may be due to high frequency specialist trading strategies that operate in trade time rather than calendar time. In sum, the estimated coefficients on *InvPrice* are consistent with the first of our main hypotheses, that higher frequency profits will increase more for low price stocks due to the greater reduction in the cost of stepping ahead.

Similarly, the estimated coefficient for *ΔInvSpreadInTicks* is positive and significant in the high frequency profit regressions for stocks in each size category in the trade time domain (Panel A). It is also positive and significant in the trade time medium frequency (10-100 trades) profit regressions for mid-cap and large stocks. In the calendar time domain it is significant for only the small stocks. This evidence is strongly consistent with our second main hypothesis, that decimalization will increase specialist profits at higher frequencies most in stocks for which the opportunities to step ahead most increase.

In the large stock sample, the estimated coefficient for *ΔInvSpreadInTicks* is positive and significant in the trade time high frequency profit regression, but not the corresponding calendar

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[30] The maximum likelihood estimates are at corner solutions with $\tau^2 = 0$ for several regressions. For these models, and for those for which interior solutions were obtained, the reported R^2, and certainly not the adjusted R^2 that we report, is not bounded below at 0.

regression. The difference is probably due to the fact that the high frequency calendar profits (less than ½ day) encompasses many more trades than do the high and medium frequency trade time profits (less than 10 or 100 trades) for these highly active stocks.[31]

We were surprised to discover that the coefficient on *ΔRelSpread* (change in quoted spread as a fraction of price) was not significantly positive in all of the high frequency profit regressions. It is significantly positive in the small stock trade time regressions, otherwise it was near zero. Thus, in several of the regressions, cross-sectional variation in the change in quoted spreads did not substantially explain cross-sectional variation in high frequency specialist profits, after accounting for changes in the cost of stepping ahead and in the opportunities for stepping ahead.[32]

In all of the high frequency regressions, the estimated volatility and non-block volume coefficients were significantly positive, as expected. The return variable generally is not statistically significant.

The estimated intercept coefficient in all the high frequency profit regressions is significantly negative. If the control variables in the regression adequately control for all factors that significantly determine specialist profits, we can interpret this result as we interpreted the parallel result for the specialist trade participation rate. Following decimalization, high frequency specialist profits would have dropped substantially if specialists could not have stepped ahead at a decreased cost and if they could not have taken advantage of the new price points. The drop in specialist profits would have been due to increased competition from limit order traders and their tightening of the spreads. As it was, specialist profits dropped for the higher priced stocks, but not by as much as they would have if specialist trading opportunities had not increased.

The estimated intercept coefficients indicate by how much high frequency specialist profits rates would have decreased if decimalization had not relaxed the negative obligations. The trading time regressions indicate that specialist high frequency profits would have dropped

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[31] As a control experiment, we estimated the same regression using the decimal pilot stock sample. In this sample, the change in high frequency profits is unrelated to both *ΔInvSpreadInTicks* and *InvPrice* and the sign and qualitative significance of the control variables is the same as observed for our primary samples. Our primary results thus are not likely due to unidentified phenomena that are unrelated to decimalization.

[32] We also estimated the model using OLS. Our results were qualitatively similar.

by 8.7, 20, and 45.9 percent, respectively for small, mid-cap, and large stocks, while the calendar time regressions indicate drops of 12.7, 22.1, and 62.6 percent. Although the different results suggest that these predictions are noisy, these results clearly indicate that the profits would have dropped.

6. Conclusion

Decimalization had three main effects on specialists. The decrease in the minimum price increment constrained their trading by allowing public limit order traders to tighten spreads, it decreased the costs of stepping ahead, and it increased the number of opportunities to step ahead. These effects had the most significant impact on low price stocks and on stocks that were commonly quoted with one-tick spreads before decimalization.

The results in this study show that specialist participation rates increased following decimalization. As expected, the increases were greatest for low price stocks and stocks for which the number of opportunities to step ahead increased.

The changes in specialist trading opportunities also affected specialist profits. Our results show that high frequency specialist trading profits increased following decimalization for low price stocks and for stocks for which the number of opportunities to step ahead increased.

If decimalization had not effectively relaxed the public precedence rule and given specialists more price points upon which to trade, the increased competition from limit order traders would have decreased specialist participation rates and specialist profits. Anyone who had hoped that decimalization would have shifted power from specialists to public traders probably failed to recognize that decimalization relaxed the negative obligations that constrain specialist trading.

In closing, we note that New York Stock Exchange specialists assume special obligations and receive special privileges in order to promote continuous liquid markets. All traders appreciate the liquidity that specialists provide but many resent their special privileges. The privileges are valuable to specialists and hence costly to other traders. Through formal or informal processes, the NYSE therefore must ensure that the benefits and costs of the specialist system are in balance. Studies such as this one are essential inputs into the regulatory process.

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Table 1

Change in price, spread, and trading activity distributions around decimalization

The data come from the NYSE Trade and Quote (TAQ) files and the NYSE Consolidated Equity Audit Trail (CAUD) files. The sample contains two three-week periods that are both roughly one-month removed from the decimalization of prices on January 29, 2001. The pre-decimalization sample contains 15 trading days from December 4 to December 22, 2000. The post-decimalization sample contains 15 trading days from February 26 to March 16, 2001. Stocks do not appear in the sample if they were included in the pilot decimal program, if they are an ADR, GDR, or Canadian issue, if their stock split during or between the sample periods, if the stock mean price exceeds $200, and if large changes in volume or returns could not be verified. The final sample contains 1,811 NYSE-listed common stocks: 1,311 small stocks, 400 mid-cap stocks, and 100 large stocks.

Panel A: Changes in market capitalization, price, and return distributions

		Small stocks		Mid-cap stocks		Large stocks	
Variable	Period	Mean	Median	Mean	Median	Mean	Median
Market cap ($million)	Pre	550.0	359.9	5,813.6	4,523.1	63,765.6	39,834.2
Price ($)	Pre	17.2	13.7	37.4	35.3	55.0	51.8
	Post	18.6	14.9	38.2	35.8	51.8	48.6
	Change	1.4	1.1	0.8	1.1	-3.2	-2.1
	(*t*- or *Z*-value)	(14.7)**	(3.6)**	(2.6)**	(0.9)	(-3.5)**	(-1.1)
Return (%)	Pre	1.8	2.1	3.1	3.8	3.6	2.1
	Post	-2.5	-1.3	-3.6	-2.8	-6.7	-5.9
	Change	-4.3	-3.4	-6.7	-6.4	-10.3	-8.5
	(*t*- or *Z*-value)	(-10.5)**	(-13.2)**	(-9.4)**	(-10.3)**	(-8.6)**	(-6.8)**
Return std. dev. (%)	Pre	2.8	2.3	3.1	2.6	3.2	2.7
	Post	2.1	1.7	2.4	2.2	2.9	2.5
	Change	-0.7	-0.5	-0.7	-0.6	-0.3	-0.4
	(*t*- or *Z*-value)	(-14.5)**	(-9.9)**	(-8.9)**	(-6.3)**	(-2.1)*	(-2.2)*

[*] Single and double asterisks respectively indicate statistical significance at the 10 and 1 percent levels.

Table 1 - continued

Panel B: Changes in spread distributions

		Small stocks		Mid-cap stocks		Large stocks	
Variable	Period	Mean	Median	Mean	Median	Mean	Median
Spread in ticks	Pre	2.3	2.1	2.1	1.9	2.2	1.9
	Post	10.8	9.7	8.6	8.1	8.7	7.7
	Change	8.5	7.4	6.5	6.0	6.5	5.6
	(*t*- or *Z*-value)	(62.0)**	(43.7)**	(44.3)**	(24.2)**	(16.1)**	(12.0)**
Quoted spread (¢)	Pre	14.4	13.0	13.2	12.3	13.5	12.1
	Post	10.8	9.7	8.6	7.9	8.7	7.7
	Change	-3.6	-3.6	-4.6	-4.5	-4.8	-4.6
	(*t*- or *Z*-value)	(-36.2)**	(-19.4)**	(-33.6)**	(-17.3)**	(-28.5)**	(-9.2)**
Effective spread (¢)	Pre	10.1	9.0	8.8	8.2	8.6	7.8
	Post	7.7	6.9	6.1	5.6	5.9	5.3
	Change	-2.3	-2.4	-2.7	-2.7	-2.7	-2.7
	(*t*- or *Z*-value)	(-32.7)**	(-19.4)**	(-25.1)**	(-16.4)**	(-19.1)**	(-8.3)**
Percentage quoted spread (basis points)	Pre	124.6	93.5	41.8	36.8	27.1	24.3
	Post	82.5	60.3	25.4	23.1	17.9	15.7
	Change	-42.1	-29.5	-16.4	-13.8	-9.1	-8.0
	(*t*- or *Z*-value)	(-28.1)**	(-16.4)**	(-21.7)**	(-16.3)**	(-13.1)**	(-7.9)**
Percentage effective spread (basis points)	Pre	88.1	67.9	28.3	24.5	17.3	15.1
	Post	59.0	44.4	18.0	16.2	12.2	10.6
	Change	-29.1	-19.1	-10.3	-8.7	-5.1	-4.1
	(*t*- or *Z*-value)	(-25.4)**	(-15.6)**	(-16.9)**	(-14.7)**	(-11.2)**	(-7.0)**
Time at inside quote (%)	Pre	30.9	28.7	40.3	38.4	40.9	40.7
	Post	6.1	4.7	11.3	10.6	11.0	10.7
	Change	-24.8	-22.3	-29.0	-27.5	-29.9	-29.6
	(*t*- or *Z*-value)	(-52.5)**	(-37.1)**	(-44.6)**	(-23.1)**	(-27.6)**	(-11.8)**

[*] Single and double asterisks respectively indicate statistical significance at the 10 and 1 percent levels.

Table 1 - continued

Panel C: Changes in trading activity distributions

Variable	Period	Small stocks Mean	Small stocks Median	Mid-cap stocks Mean	Mid-cap stocks Median	Large stocks Mean	Large stocks Median
Transactions	Pre	111.6	51.5	770.4	641.6	3,029.1	2,425.2
(per day)	Post	128.6	56.5	952.7	815.1	3,518.6	2,955.3
	Change	17.0	1.0	182.3	142.2	489.5	413.7
	(*t*- or *Z*-value)	(7.5)**	(0.4)	(12.7)**	(4.5)**	(5.2)**	(2.5)*
Share volume	Pre	350.7	98.9	3,274.3	1,771.3	23,735.9	14,867.0
(1,000s per day)	Post	294.5	75.5	2,889.1	1,739.9	25,210.5	11,338.5
	Change	-56.2	-11.2	-385.2	-60.9	1,474.6	-37.3
	(*t*- or *Z*-value)	(-2.8)**	(-4.1)**	(-1.9)*	(-0.4)	(0.6)	(-0.6)
Block volume	Pre	206.9	27.2	2,167.6	869.8	18,317.2	9,814.5
(1,000s per day)	Post	156.5	19.2	1,637.7	715.6	18,827.5	6,596.5
	Change	-50.4	-3.4	-529.9	117.0	510.3	-559.3
	(*t*- or *Z*-value)	(-2.7)**	(-4.4)**	(-2.8)**	(-1.8)*	(0.2)	(-1.3)
Non-block volume	Pre	143.9	62.6	1,106.6	837.4	5,418.7	4,369.7
(1,000s per day)	Post	138.0	49.4	1,251.4	912.0	6,683.0	4,965.0
	Change	-5.9	-6.2	144.8	56.0	964.3	555.2
	(*t*- or *Z*-value)	(-1.6)	(-3.4)**	(5.2)**	(1.6)	(4.8)**	(1.7)*

[*] Single and double asterisks respectively indicate statistical significance at the 10 and 1 percent levels.

Table 2

Change in specialist participation rates

Mean percentage of shares traded with specialist participation, and mean percentage of transactions with specialist participation, for all stocks and trades, by stock price level, and by price relative to the prevailing quote. We include the pair-wise *t*-test to consider whether the mean change in participation rates is significantly different after decimalization. The sample contains 1,811 NYSE-listed common stocks; the numbers of observations in the price-size sorted subsamples are noted in the table.

Panel A: Change in specialist share and trade participation rates

Sample set		Small stocks		Mid-cap stocks		Large stocks	
		Shares	Trades	Shares	Trades	Shares	Trades
All stocks	Pre	17.7	35.9	9.8	27.4	6.8	24.3
	Post	22.1	43.3	11.8	32.4	8.3	30.0
	Change	4.4	7.4	2.0	5.0	1.5	5.7
	t-stat	(15.5)**	(24.7)**	(9.1)**	(15.8)**	(4.6)**	(10.1)**
	N	1,311	1,311	400	400	100	100
By price level:							
Low	Pre	15.4	32.5	4.5	17.6	-	-
(< $10)	Post	21.2	43.3	9.6	31.0	-	-
	Change	5.8	10.8	5.1	13.4	-	-
	t-stat	(11.2)**	(18.2)**	(7.5)**	(7.4)**	-	-
	N	403	403	9	9	0	0
Mid	Pre	18.3	36.4	7.7	23.7	4.4	18.1
($10-$25)	Post	22.6	43.4	10.8	31.6	5.3	28.7
	Change	4.3	7.0	3.1	7.9	0.9	10.6
	t-stat	(10.3)**	(16.6)**	(5.9)**	(10.7)**	(1.3)	(6.5)**
	N	645	645	95	95	6	6
High	Pre	19.9	39.7	10.6	28.9	6.9	24.7
(> $25)	Post	22.4	43.3	12.1	32.7	8.5	30.1
	Change	2.5	3.6	1.5	3.8	1.6	5.4
	t-stat	(4.5)**	(7.1)**	(6.5)**	(11.9)**	(4.4)**	(9.3)**
	N	263	263	296	296	94	94

* Single and double asterisks respectively indicate statistical significance at the 10 and 1 percent levels.

Table 2 - continued

Panel B: Change in percentage of specialist trades by trade price relative to quote

Sample set		Small stocks		Mid-cap stocks		Large stocks	
		At quote	Inside quote	At quote	Inside quote	At quote	Inside quote
All stocks	Pre	44.1	55.6	42.6	56.8	39.8	59.2
	Post	33.3	66.0	31.1	67.7	28.2	70.1
	Change	-10.7	10.4	-11.5	10.9	-11.6	10.9
	t-stat	(-36.9)**	(35.6)**	(-39.4)**	(37.1)**	(-18.6)**	(17.3)**
	N	1,311	1,311	400	400	100	100
By price level:							
Low	Pre	44.9	54.8	43.1	56.7	-	-
(< $10)	Post	34.5	65.0	31.3	67.9	-	-
	Change	-10.4	10.2	-11.8	11.2	-	-
	t-stat	(-18.6)**	(18.1)**	(-4.6)**	(4.5)**	-	-
	N	403	403	9	9	0	0
Mid	Pre	43.6	56.1	43.5	56.1	43.1	56.4
($10-$25)	Post	32.7	66.6	30.7	68.3	27.4	71.5
	Change	-10.9	10.5	-12.8	12.2	-15.7	15.1
	t-stat	(-25.4)**	(24.4)**	(-19.5)**	(18.5)**	(-13.9)**	(15.2)**
	N	645	645	95	95	6	6
High	Pre	43.9	55.6	42.2	57.1	39.6	59.4
(> $25)	Post	33.2	65.9	31.2	67.5	28.3	70.1
	Change	-10.7	10.3	-11.0	10.4	-11.3	10.7
	t-stat	(-21.3)**	(20.5)**	(-34.3)**	(32.2)**	(-17.5)**	(16.2)**
	N	263	263	296	296	94	94

[*] Single and double asterisks respectively indicate statistical significance at the 10 and 1 percent levels.

Table 3

Cross sectional determinants of the change in specialist participation rates

The dependent variable is the change in percentage of transactions with specialist participation. *InvPrice* is the inverse of price, *ΔInvSpreadInTicks* is the change in the time-weighted mean spread in ticks, *ΔVolatility* is the change in mean daily return standard deviation, *ΔReturn* is the change in return, *ΔNonBlockVolume*, and *ΔBlockVolume* are the changes in non-block and block volume, respectively, where a trade greater than 10,000 shares is considered a block. Each cell reports the maximum likelihood estimate and t-statistic estimated from (1).

	Stock sample		
	Small	Mid-cap	Large
Intercept	-0.092	-0.132	-0.141
	(-11.3)**	(-10.8)**	(-5.4)**
InvPrice	0.119	0.461	0.200
	(4.3)**	(3.7)**	(0.4)
ΔInvSpreadInTicks	0.433	0.449	0.509
	(19.3)**	(12.5)**	(6.7)**
ΔVolatility	0.003	-0.001	-0.005
	(2.3)*	(-1.2)	(-1.7)*
ΔNonBlockVolume	-0.001	-0.001	-0.001
	(-3.9)**	(-2.0)*	(-3.0)**
ΔBlockVolume	-0.000	-0.000	-0.000
	(-0.0)	(-0.78)	(-1.3)
ΔReturn	-0.001	-0.001	-0.001
	(-0.9)	(-2.8)**	(-3.1)**
Adjusted R^2	0.25	0.43	0.46
Observations	1,311	400	100

[*] Single and double asterisks respectively indicate statistical significance at the 10 and 1 percent levels.

Table 4

The effective spread and price improvement of specialist trades

We provide the mean effective spread (in cents) of all specialist trades, by price relative to the prevailing quote, and by stock price level. We include the pair-wise *t*-test to consider whether the mean change in specialist effective spreads is significantly different after decimalization. The total sample contains 1,811 stocks. None of the top 100 largest stocks have prices below 10 dollars.

Panel A: Specialist effective spreads by firm size

		Specialist effective spreads (¢)			Price
Sample		All trades	At quote	Inside quote	Improvement
Small stocks	Pre	8.9	13.5	5.0	8.7
N=1,311	Post	7.8	10.0	6.4	5.8
	Change	-1.1	-3.5	1.4	-2.9
	t-stat	(-13.4)**	(-33.8)**	(18.6)**	(-45.6)**
Mid-cap stocks	Pre	8.0	12.5	4.5	8.5
N=400	Post	6.4	8.0	5.5	5.2
	Change	-1.6	-4.5	1.0	-3.3
	t-stat	(-15.9)**	(-37.1)**	(10.4)**	(-44.2)**
Large stocks	Pre	7.4	12.0	3.9	8.2
N=100	Post	5.9	7.7	4.8	4.3
	Change	-1.5	-4.3	0.9	-3.9
	t-stat	(-7.6)**	(-26.8)**	(3.9)**	(-22.3)**

* Single and double asterisks respectively indicate statistical significance at the 10 and 1 percent levels.

Table 4 - continued

Panel B: Specialist effective spreads by firm size and price level

		Specialist effective spreads (¢)			Price
		All trades	At quote	Inside quote	Improvement
Small stocks					
Low	Pre	6.6	10.8	3.1	7.6
(< $10)	Post	6.1	8.0	5.0	4.6
N=403	Change	-0.5	-2.8	1.9	-3.0
	t-stat	(-4.1)**	(-19.4)**	(19.1)**	(-38.7)**
Mid	Pre	8.9	13.6	5.0	8.6
($10 — $25)	Post	7.7	9.9	6.3	5.6
N=645	Change	-1.2	-3.7	1.3	-3.0
	t-stat	(-11.2)**	(-26.5)**	(13.3)**	(-44.2)**
High	Pre	12.3	17.6	7.8	10.8
(> $25)	Post	10.5	13.5	8.6	8.4
N=263	Change	-1.8	-4.1	0.8	-2.4
	t-stat	(-7.2)**	(-13.1)**	(3.4)**	(-10.1)**
Mid-cap stocks					
Low	Pre	3.3	7.0	0.4	6.4
(< $10)	Post	2.5	3.3	2.1	2.5
N=9	Change	-0.8	-3.7	1.7	-3.9
	t-stat	(-1.9)*	(-10.2)**	(6.1)**	(-12.7)**
Medium	Pre	5.8	9.7	2.7	7.5
($10 — $25)	Post	4.7	5.9	4.1	3.9
N=95	Change	-1.1	-3.8	1.4	-3.6
	t-stat	(-7.6)**	(-26.9)**	(11.3)**	(-50.5)**
High	Pre	8.9	13.5	5.2	8.9
(> $25)	Post	7.1	8.8	6.0	5.7
N=296	Change	-1.8	-4.7	0.8	-3.2
	t-stat	(-14.3)**	(-30.5)**	(7.0)**	(-32.9)**

* Single and double asterisks respectively indicate statistical significance at the 10 and 1 percent levels.

Table 4, Panel B - continued

		Specialist effective spreads (¢)			Price Improvement
		All trades	At quote	Inside quote	
Large stocks					
Mid	Pre	4.3	8.4	1.0	6.6
($10 – $25)	Post	3.0	4.4	2.4	2.4
N=6	Change	-1.3	-4.0	1.4	-4.2
	t-stat	-5.3**	-13.1**	6.7**	-19.1**
High	Pre	7.6	12.2	4.1	8.3
(> $25)	Post	6.1	7.9	5.0	4.5
N=94	Change	-1.5	-4.3	0.9	-3.8
	t-stat	-7.2**	-25.4**	3.6**	-20.8**

[*] Single and double asterisks respectively indicate statistical significance at the 10 and 1 percent levels.

Table 5

Comparison of gross specialist profit distributions

Profits are measured on a mark-to-market basis assuming zero specialist inventories at the beginning of each sample period using equation (3). Gross profits are the sum of the mark-to-market profits over each period stated on a per day basis. The sample contains 1,811 stocks: 1,311 small stocks, 400 mid-cap stocks, and 100 large stocks.

		Small stocks		Mid-cap stocks		Large stocks	
	Period	Mean	Median	Mean	Median	Mean	Median
Gross profits	Pre	5.4	2.2	139.2	53.6	495.0	282.1
($1,000 per day)	Post	5.2	2.3	26.7	30.3	150.8	261.2
	Change	-0.2	0.4	-112.5	-33.9	-344.2	-6.1
	(*t*- or *Z*-value)	(-0.1)	(0.8)	(-3.5)**	(-3.1)**	(-1.7)*	(-0.7)

* Single and double asterisks respectively indicate statistical significance at the 10 and 1 percent levels.

Table 6

Comparison of gross specialist profit distributions

Profits are measured on a mark-to-market basis assuming zero specialist inventories at the beginning of each sample period using equation (3). Gross profits are decomposed into high, medium, and low frequency components using the spectral methods described in Section 5.3. The full samples are used for each panel (1,311 small stocks; 400 mid-cap stocks; 100 large stocks).

Panel A: Profits decomposed by trade frequencies ($1,000s)

		Small stocks		Mid-cap stocks		Large stocks	
Frequency	Period	Mean	Median	Mean	Median	Mean	Median
High	Pre	12.6	6.4	82.6	58.4	359.0	280.7
(< 10 trades)	Post	11.6	5.5	73.5	54.8	316.9	252.4
	Change	-1.0	-0.3	-9.1	-2.7	-42.1	-21.4
	(*t*- or *Z*-value)	(-2.3)*	(-1.7)*	(-3.2)**	(-0.8)	(-3.2)**	(-1.2)
Medium	Pre	10.8	2.3	95.0	55.6	452.5	344.4
(10 — 100 trades)	Post	9.8	2.5	75.6	51.2	388.7	281.3
	Change	-1.0	0.1	-19.4	-6.1	-63.8	-43.1
	(*t*- or *Z*-value)	(-1.6)	(0.8)	(-4.8)**	(-1.1)	(-3.0)**	(-1.8)*
Low	Pre	-18.1	-2.4	-38.4	-26.0	-316.5	-229.9
(> 100 trades)	Post	-16.2	-1.3	-122.3	-50.7	-554.8	-176.9
	Change	1.8	0.3	-83.9	-25.3	-238.3	35.2
	(*t*- or *Z*-value)	(0.6)	(1.1)	(-2.6)*	(-3.3)**	(-1.2)	(0.4)

Panel B: Profits decomposed by calendar frequencies ($1,000s)

		Small stocks		Mid-cap stocks		Large stocks	
Frequency	Period	Mean	Median	Mean	Median	Mean	Median
High	Pre	23.2	7.2	189.9	116.0	865.4	645.4
(< ½-day period)	Post	22.2	6.8	155.6	112.7	719.1	490.6
	Change	-1.0	0.0	-34.3	-7.4	-146.3	-73.7
	(*t*- or *Z*-value)	(-0.8)	(0.3)	(-3.8)**	(-1.0)	(-3.9)**	(-1.8)*
Medium	Pre	2.0	1.4	-18.0	-5.8	-167.3	-105.7
(½ — 3-day period)	Post	-0.6	1.0	-23.0	-10.3	-76.1	-49.4
	Change	-2.6	-0.4	-5.0	-1.4	91.2	51.4
	(*t*- or *Z*-value)	(-3.1)**	(-3.4)**	(-0.8)	(-0.7)	(2.4)*	(2.8)**
Low	Pre	-19.7	-2.9	-32.6	-19.6	-203.1	-165.7
(> 3 day-period)	Post	-16.4	-1.6	-105.8	-45.1	-492.2	-110.9
	Change	3.3	0.5	-73.2	-19.3	-289.1	-5.0
	(*t*- or *Z*-value)	(1.0)	(1.2)	(-2.3)*	(-3.2)**	(-1.4)	(-0.1)

* Single and double asterisks respectively indicate statistical significance at the 10 and 1 percent levels.

Table 7

Cross sectional determinants of the change in specialist profits

The dependent variable is the change in specialist profits expressed as a fraction of expected profits estimated using (11). Profits are decomposed into high, medium, and low frequency components using the spectral methods described in Section 5.3. *InvPrice* is the inverse of the mean price in the pre-decimalization period. *ΔInvSpreadInTicks* is the change in the inverse time-weighted spread measured in ticks. *ΔRelSpread* is the change in the quoted spread relative to price. *ΔVolatility* is the change in the standard deviation of daily returns. *RelΔNonBlockVolume* and *RelΔBlockVolume* are the changes in non-block and block volume, respectively, expressed as a fraction of expected profits. Trades over 10,000 shares are considered a block. $\hat{\tau}^2$ and $\hat{\gamma}^2$ are the estimated variance component coefficients of equation (13). If $\hat{\tau}^2 = 0$, the estimates are equivalent to GLS estimates. If $\hat{\gamma}^2 = 0$, the estimates are equivalent to OLS estimates, otherwise the estimates are maximum likelihood estimates. Each cell reports the coefficient estimate and *t*-statistic estimated from equation (12).

Panel A: Trade time profit components

	Small stock sample regressions			Mid-cap stock sample regressions			Large stock sample regressions		
	High	Medium	Low	High	Medium	Low	High	Medium	Low
Intercept	-0.087	-0.003	-0.013	-0.200	-0.248	0.165	-0.459	-0.649	0.778
	(-8.3)**	(-0.3)	(-0.8)	(-4.2)**	(-3.0)**	(1.1)	(-3.5)**	(-3.4)**	(0.5)
InvPrice	0.352	-0.022	0.075	2.048	1.289	7.855	-0.463	-12.318	-38.821
	(4.8)**	(-0.3)	(0.5)	(3.1)**	(1.1)	(2.2)*	(-0.1)	(-1.8)*	(-0.7)
ΔInvSpreadInTicks	0.248	0.027	0.009	0.357	0.487	-1.235	0.981	1.333	-2.454
	(8.9)**	(1.1)	(0.3)	(2.6)**	(2.0)*	(-2.2)*	(2.5)**	(2.3)*	(-0.5)
ΔRelSpread	0.000	0.000	-0.001	0.001	0.000	0.005	-0.004	-0.025	-0.107
	(4.1)**	(0.35)	(-0.7)	(1.1)	(0.0)	(1.11)	(-0.6)	(-2.2)*	(-1.2)
ΔVolatility	0.017	0.008	-0.023	0.051	0.092	-0.084	0.040	0.001	-0.041
	(5.2)**	(2.1)*	(-2.4)*	(5.4)**	(5.7)**	(-1.5)	(2.8)**	(0.05)	(-0.2)
RelΔNonBlockVolume	2.690	0.641	-0.461	1.787	2.541	-2.458	1.012	3.797	3.892
	(12.8)**	(2.8)**	(-1.3)	(7.6)**	(6.3)**	(-1.3)	(2.7)**	(6.4)**	(0.8)
RelΔBlockVolume	-0.003	-0.608	0.381	0.062	-0.085	0.354	0.039	0.075	-0.963
	(-0.1)	(-10.9)**	(2.6)**	(2.0)*	(-1.6)	(1.3)	(0.6)	(0.8)	(-1.3)
ΔReturn	-0.001	-0.001	0.003	-0.001	0.000	0.011	-0.001	-0.001	0.016
	(-1.8)*	(-1.4)	(2.4)*	(-0.87)	(0.52)	(2.2)*	(-0.8)	(-0.4)	(0.9)
$\hat{\tau}^2$	0.01	0.01	0.00	0.01	0.03	0.00	0.01	0.00	0.00
$\hat{\gamma}^2$	0.03	0.09	1.03	0.01	0.02	0.91	0.01	0.01	0.76
Adjusted R^2	0.32	-0.13	-0.01	0.22	0.21	0.03	0.02	0.05	0.02
Observations	1,311	1,311	1,311	400	400	400	100	100	100

[*] Single and double asterisks respectively indicate statistical significance at the 10 and 1 percent levels.

Table 7 - continued

Panel B: Calendar time profit components

	Small stock sample regressions			Mid-cap stock sample regressions			Large stock sample regressions		
	High	Medium	Low	High	Medium	Low	High	Medium	Low
Intercept	-0.127	0.008	-0.009	-0.221	-0.035	0.171	-0.626	0.257	0.183
	(-7.4)**	(0.8)	(-0.5)	(-2.0)**	(-0.8)	(1.2)	(-1.7)*	(0.7)	(0.1)
InvPrice	0.496	0.147	-0.039	3.934	-1.103	7.631	-32.309	11.954	-30.617
	(3.9)**	(1.9)*	(-0.2)	(2.4)*	(-1.0)	(2.2)*	(-2.5)*	(1.0)	(-0.6)
ΔInvSpreadInTicks	0.345	-0.023	0.018	0.307	0.177	-1.277	1.766	-1.140	-1.208
	(8.1)**	(-0.9)	(0.6)	(0.9)	(1.06)	(-2.3)*	(1.5)	(-1.0)	(-0.3)
ΔRelSpread	0.000	0.001	-0.001	0.001	-0.000	0.005	-0.054	0.022	-0.101
	(0.74)	(6.8)**	(-1.8)*	(0.5)	(-0.11)	(0.9)	(-2.5)*	(1.1)	(-1.1)
ΔVolatility	0.025	-0.004	-0.020	0.116	-0.012	-0.078	0.098	-0.132	0.012
	(4.2)**	(-1.0)	(-2.0)*	(4.7)**	(-0.71)	(-1.4)	(2.2)*	(-3.2)**	(0.1)
RelΔNonBlockVolume	4.049	0.385	-0.680	3.073	0.661	-2.366	2.229	1.835	4.001
	(12.5)**	(1.7)*	(-1.8)*	(4.4)**	(1.2)	(-1.3)	(1.9)*	(1.7)*	(0.8)
RelΔBlockVolume	-0.011	-0.866	0.595	0.129	-0.348	0.570	0.201	-0.208	-0.804
	(-0.1)	(-15.6)**	(3.9)**	(1.3)	(-4.2)**	(2.1)*	(1.1)	(-1.2)	(-1.1)
ΔReturn	-0.001	-0.001	0.004	0.001	0.000	0.010	-0.002	-0.014	0.027
	(-2.9)**	(-1.7)*	(3.1)**	(0.7)	(0.16)	(1.9)*	(-0.5)	(-2.9)**	(1.5)
$\hat{\tau}^2$	0.01	0.01	0.00	0.02	0.00	0.00	0.01	0.04	0.00
$\hat{\gamma}^2$	0.13	0.09	1.13	0.09	0.08	0.86	0.04	0.03	0.72
Adjusted R^2	0.21	0.03	-0.01	0.06	0.02	0.03	-0.03	-0.04	0.02
Observations	1,311	1,298	1,180	400	400	400	100	100	100

* Single and double asterisks respectively indicate statistical significance at the 10 and 1 percent levels.

Figure 1

Distribution of market capitalization

The log market value of each stock is plotted in descending order, along with the cumulative market capitalization. Market capitalization is computed using the mean price during the three-week pre-decimalization period and the number of shares outstanding at the end of December 2000. Our sample is divided into three capitalization subsamples, using the 100 and 500 stock ranks as breakpoints. *N*=1,811.